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Research Paper

Did community greening reduce crime? Evidence from New Haven, CT, 1996–2007

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HIGHLIGHTS

- The relationship between community-based tree planting and crime is understudied.
- A quasi-experimental approach revealed predominantly null findings.
- Imprecise measurement of treatment and exposure need more careful consideration.

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ABSTRACT

For some volunteers, neighborhood safety is one of the reasons for becoming involved in community greening. For example, many volunteers of the Community Greenspace program at the Urban Resources Initiative in New Haven, Connecticut believe that there is a potential reduction in crime from community greening activities, even though it is not an explicit goal of the program. These types of community-led interventions are distinct from both existing tree canopy and large-scale municipally led initiatives. These types of interventions remain understudied with respect to the potential for reducing crime. We therefore used a quasi-experimental difference-in-differences (DID) approach to test whether more than a decade of street tree planting (1996–2007) in New Haven had an effect on crime levels at planting sites ($n = 300$) compared to control sites that received no Community Greenspace-planted trees ($n = 893$). We examined violent, property, and misdemeanor crimes (comprised of vandalism, prostitution, and narcotics crimes) individually and jointly to test for crime-type specific effects, while controlling for sociodemographic factors and spatio-temporal trends. In general, we found a null relationship between trees planted and crime on block faces per year at the $p < 0.05$ level. Increases in crime were not observed on treatment sites. We discuss implications for tree inventories and monitoring, study design, and techniques to assess impacts of tree planting efforts.

1. Introduction

Dozens of cities across the US are embarking on ambitious tree planting campaigns that aim to significantly increase canopy in hopes of improving urban sustainability and livability (Young & McPherson, 2013). Many of these programs are motivated by the theory that increasing tree canopy will also improve community safety. Studies have reported mixed results with respect to the relationship between urban vegetation and crime; early research suggests bushes and shrubs may provide criminals with places to conceal themselves and/or illegal contraband (Fisher & Nasar, 1992; Michael, Hull, & Zahm, 2001; Nasar, Fisher, & Grannis, 1993). However, recent studies have shown a negative association between presence of trees or tree canopy and crime (e.g. Gilstad-Hayden et al., 2015; Troy, Grove, & O'Neil-Dunne, 2012). Some theorize that the social processes associated with greening, namely enhanced

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territoriality, could be a causal mechanism for crime reduction (Kuo and Sullivan, 2001a). But there appears to be little empirical investigation on the topic. Research is needed to examine the possible influence of community-based greening on crime.

Community-based greening activities are driven by the goals of volunteers rather than government agencies and municipal sustainability plans. For example, the Community Greenspace program at the Urban Resources Initiative (URI) in New Haven, CT supports projects initiated by volunteers who identify where and what activities they wish to pursue–not government agencies, nor their sustainability plans. These activities include, for example, street tree planting in the public right-of-way, lead remediation and beautification in private front yards, stewardship and planting in city parks, and reclamation of abandoned vacant lots (Murphy-Dunning 2009). Volunteers are sometimes motivated to become involved in community greening because they hope this activity will result in making their neighborhood safer. In this study we use a quasi-experimental difference-in-differences (DID) approach to test for effects of a community-based greening in New Haven, CT on crime from 1996 to 2007 at greened street segments in comparison to randomly matched non-greened control segments.

1.1. Previous research

Early investigations into the relationship between urban vegetation and crime suggest that areas of low-lying vegetation may host criminal activity (Fisher and Nasar, 1992; Michael et al., 2001; Nasar et al., 1993), and therefore may increase crime. This could cast doubt on urban greening programs that seek to increase vegetation, e.g. via green infrastructure installations. However, the role of low-lying vegetation in crime should be viewed as distinct from the role of other types of urban vegetation, such as trees.

Subsequent research employing cross-sectional designs with aggregate data establishes a negative association between urban vegetation and crime. For example, fewer total crimes, property crimes, and vandalism co-occurred when more street trees, trees on residential lots, and where bigger crowned trees were present in Portland, OR (Donovan and Prestemon, 2012). Wolfe and Mennis (2012) found a negative relationship in Philadelphia, PA between urban greenness and robberies, burglaries, and aggravated assaults, but not thefts when controlling for other confounders. A negative association between robbery, burglary, theft and shooting crimes and tree canopy cover was found in a study of Baltimore City and County (Troy et al., 2012). A subsequent study in Baltimore found a strong association between front yard landscaping, including presence of yard trees and other "cues to care" (Nassauer, 1995), and an index of crimes including robbery, burglary, theft, assault, vandalism, arson, and shooting crimes (Troy, Nunery, & Grove, 2016). Deng (2015) found a negative association between tree height and mean tree patch size with property crimes, and between tree abundance and violent crimes. Previous research in New Haven found 15% fewer violent crimes, and 14% fewer property crimes with 10% more abundant tree canopy cover (Gilstad-Hayden et al., 2015).

One explanation for a negative relationship between greenery and crime is that exposure to green space can reduce psychosocial stress, physiological stress and mental fatigue in urban settings (Kuo, 2001; Kuo & Sullivan, 2001b; Taylor & Kuo, 2009; South, Kondo, Cheney, & Branas, 2015), and stress can elevate aggressive behaviors including certain types of crime. Therefore greener environments may reduce aggressive and violent criminal activities (Kuo & Sullivan, 2001b). In this view, greenery works indirectly to reduce crime with greenery via stress reduction.

Another theory explaining the negative relationship between urban vegetation and crime is that more "eyes upon the street" makes it more difficult for criminals to elude capture with so many available known witnesses (Jacobs, 1961: 35). This idea can be extended to include urban vegetation, as more welcoming treed environments may bring people together, and increase social ties among neighbors (Kuo et al., 1998; Kuo, 2003). Some evidence suggests that community gardeners may also become involved in other activities together, including crime-watch efforts (Armstrong, 2000). Similarly, defensible space theory posits that community order can be partially maintained by the physical appearance of neighborhoods designed to facilitate community interactions, and the opportunities for informal surveillance (Newman, 1972). A third related "broken windows" theory asserts that visibly disinvested built environments encourage crime because they signal low levels of care, which provides a visual cue to would-be criminals that effective law enforcement might also be lacking (Wilson and Kelling, 1982).

These three theories challenge the assumption that trees' only relationship with crime is that they provide would-be criminals a place to hide. Instead of merely reducing visibility, these vegetated elements in the built environment may actively signal well-cared for spaces. Such "cues to care" or signifiers of human intention (Nassauer, 1995) have been found to be negatively related to criminal activity, while landscaping features indicative of neglect were positively associated with robbery and rape crimes across an urban-rural watershed (Lidman, 2008). The interrelated causal mechanisms of increasing social cohesion with more eyes upon the street, defensible space, and broken windows theories, as well as cues to care each help explain the empirical evidence showing negative correlations between urban vegetation and crime.

The newest wave of research uses experimental and quasi-experimental evidence from interventions to begin testing for effects. These research projects go beyond correlations supported by theory, and move toward testing for causality. Multiple studies of cleaning and greening interventions on vacant lots have found negative impacts on crime. One study in Philadelphia found significant reductions in gun assaults and vandalism around greened lots, compared to untreated control vacant lots (Branas et al., 2011). Similar cleaning and greening interventions have been shown to lead to a stronger sense of security and feelings of safety in Philadelphia, PA (Garvin, Cannuscio, & Branas, 2013). A study of vacant lots greened in Youngstown, OH found significant reductions in property crimes around lots greened by the city and its partners, and significant reductions in violent crimes around lots greened by community groups, compared to around control lots (Kondo, Hohl, Han, & Branas, 2015). Using similar methods, a study of crime impacts near green stormwater infrastructure projects, a type of visible and vegetation-based public investment, in Philadelphia found consistent reductions in narcotics possession near project sites compared to control sites (Kondo, Low, Henning, & Branas, 2015). Finally, the first natural experiment on the association between *tree loss* and crime (Kondo, Han, Donovan, & MacDonald, 2017) found that tree loss due to emerald ash borer infestation between 2005 and 2014 in Cincinnati, OH was significantly and positively associated with increases in property crimes and violent crimes.

Previous research does not specifically address community-based street tree planting and crime, despite the reasonable yet seemingly untested notion that "the *process* of tree planting could enhance residents' territoriality, thereby deterring crime over and above the direct effect of the presence of vegetation" (emphasis added, Kuo & Sullivan 2001b) proposed more than a decade ago. The purpose of this paper is to fill this void by asking: did community-based greening lead to a reduction in crime in New Haven, CT from 1996 to 2007? Using a quasi-experimental difference-in-differences method, we matched the locations of community-led interventions to control sites and compared crime rates over the twelve-year study period.

2. Method

New Haven is the sixth largest city in New England with respect to population. Just under 130,000 residents lived within its nineteen square miles according to the 2010 Census (United States Census Bureau, 2011). Among Connecticut's five largest cities, New Haven had the most violent crimes (~13 per 1000 people) and property crimes (~46 per 1000 people; US Department of Justice, 2013) in 2013.

In 1995, a local nonprofit organization called the Urban Resources Initiative (URI) launched a program called Community Greenspace. The Community Greenspace program provides material and technical support to community groups working to improve their neighborhoods through greening. Many of the Community Greenspace groups explicitly mention reducing crime in their project applications to URI, even though it is not an explicit goal of the of the organization. When the program first began, the City of New Haven mailed the application to blockwatch groups and several formed civic groups who planted trees. Tree planting efforts are entirely driven by residents, so the scale and number of trees to be planted and locations are based on their capacity and interest. The volunteer groups' capacity varies widely with some planting only a few trees on a block one summer, and other groups planting up to 100 trees over several years and across a broader area. Some residents green their neighborhoods by planting street trees and trees in city parks, beautifying private front yards, and transforming abandoned vacant lots into gardens, while hoping these activities will improve safety.

2.1. Data

This study employs the block face as the spatial unit of analysis. A block face, according to Ellen, Lacoe, and Sharygin (2013: 59), is "an individual street segment including properties on both sides of the street", and "is bounded by the two closest cross-streets, and which incorporates buildings on both sides of the street". This spatial unit of analysis may be preferable to straight-line distance buffers or the commonly used Census block groups. The Greenspace groups' planting locations analyzed here are constrained to the public right of way, or on otherwise adjacent lots, and occur in this zone on a block-to-block basis. The block face better approximates the lived experience in these cases. On the other hand, distance-based buffers may be inappropriate since they typically include non-visible areas in the block's core that may be spurious or inconsequential to the social and ecological processes of interest. Conditions within a Census block or block group may be considerably different across different land uses.

Data on trees planted by the Community Greenspace Program were obtained from the Urban Resources Initiative in either one of two files. The first contained the locations of street trees planted (n = 581) by members of the Community Greenspace Program described in previous studies (Jack-Scott, Piana, Troxel, Murphy-dunning, & Ashton, 2013; Troxel, Piana, Ashton, & Murphy-Dunning, 2013). The other file contained trees planted by Greenspace groups off the street in community gardens and parks (n = 792). Both files contained the year of planting and were merged together. Next these points were spatially joined to the nearest block face using ArcGIS 10.1 (ESRI, 2012). Three hundred block faces with trees planted by Greenspace were considered in the treatment group.

We restricted candidate control block faces for each treatment block face to the same geographic section of the city to ensure relatively similar site conditions (Fig. 1), but greater than ¼ mile away to reduce spill-over and contamination concerns. The remaining candidate controls were then eligible if they were within ±20% of year 2000 median household income and ±20% education of the treatment block face. The education variable was calculated as the percentage of the 25-year and older population with a high school diploma or additional educational attainment. Year 2000 is approximately the midpoint of the study. Finally, among those candidate matches we selected three block faces at random for each treatment block face. Given these criteria four sites were unmatchable and not included in the analyses, and three treatment sites only had one suitable match (one in the Western section, two in the Eastern section). One treatment site also in the Eastern section had just two suitable matches. The final sample included 300 treatment block faces and 893 control block faces.

We obtained 12 years of georeferenced, incident-level crime data (1996 through 2007) from the New Haven Police Department. Because we were interested in the possible effects of greening on different types of crime, we examined four types of crime: 1) violent, 2) property, 3) misdemeanor and 4)'All Crime' which is the sum of classes 1, 2, and 3. Misdemeanor crimes included vandalism, prostitution, and narcotics.

We obtained demographic block group-level data from the 1990 and 2000 decennial Census and the American Community Survey (ACS) 5-year estimates from 2006 to 2011. The 2006–2011 ACS data represents a rolling average for those years. Census data included percent owner-occupied housing, percentage of the 25 year and older population with a high school diploma or additional education, and the 16 year old population and older that worked last year. We included these demographic control variables because they are theoretically and empirically associated with crimes and thus commonly used in criminology literature (e.g. Farrall, Hay, Jennings, & Gray, 2015; Land, MCall, & Cohen, 1990). Other controls were considered, but not included due to concerns of overfitting with too many control variables (Babyak, 2004). We spatially joined this data to each block face. When a block face intersected two or more Census block groups, we assigned the average values. We calculated the percent values for home ownership, education and employment for 1990, 2000 and 2006/2011. We calculated year-specific demographic estimates by linearly interpolating between 1990, 2000 and 2006/2011. Because the 2006–2011 ACS represents a rolling average, we set year 2006 and 2007 values equal to the 2006–2011 ACS values. While there is a scalar miss-match between the demographic data collected by the Census Bureau and our finer unit of analysis, the block face, we used the best available data. We adjusted demographic values for regression to the mean by assigning pre-period means to the post-period, to remove double-adjusting during the post-period.

2.2. Statistical analyses

This study examines the potential effect of a community-based greening program on crime at greened street segments in comparison to matched non-greened control segments with a difference-in-differences (DID) approach. The existence of overdispersion in our outcomes may lead to incorrect conclusions from the Poisson regression model estimates; overdispersion tends to underestimate standard errors and thus inflates z-scores in a standard Poisson regression (Rabe-Hesketh and Skrondal, 2012). Therefore, using incident-level crime outcome data, we employed a negative binomial model that specifies a gamma distribution for the exponentiated random intercept (Cameron & Trivedi, 1986; Greene, 2008).

For each of the crime classes described above, we specified a marginal mean and a marginal variance from the negative binomial model:

$$E(Y_{it}|P_{it}, R_{it}, X_{it}) = \exp\left(\beta_0 + \beta_1 P_{it} + \beta_2 R_{it} + \beta_3 (P_{it} \times R_{it}) + \sum_{k=4}^{p} \beta_k X_{it} + \xi_i + \delta_t\right)$$

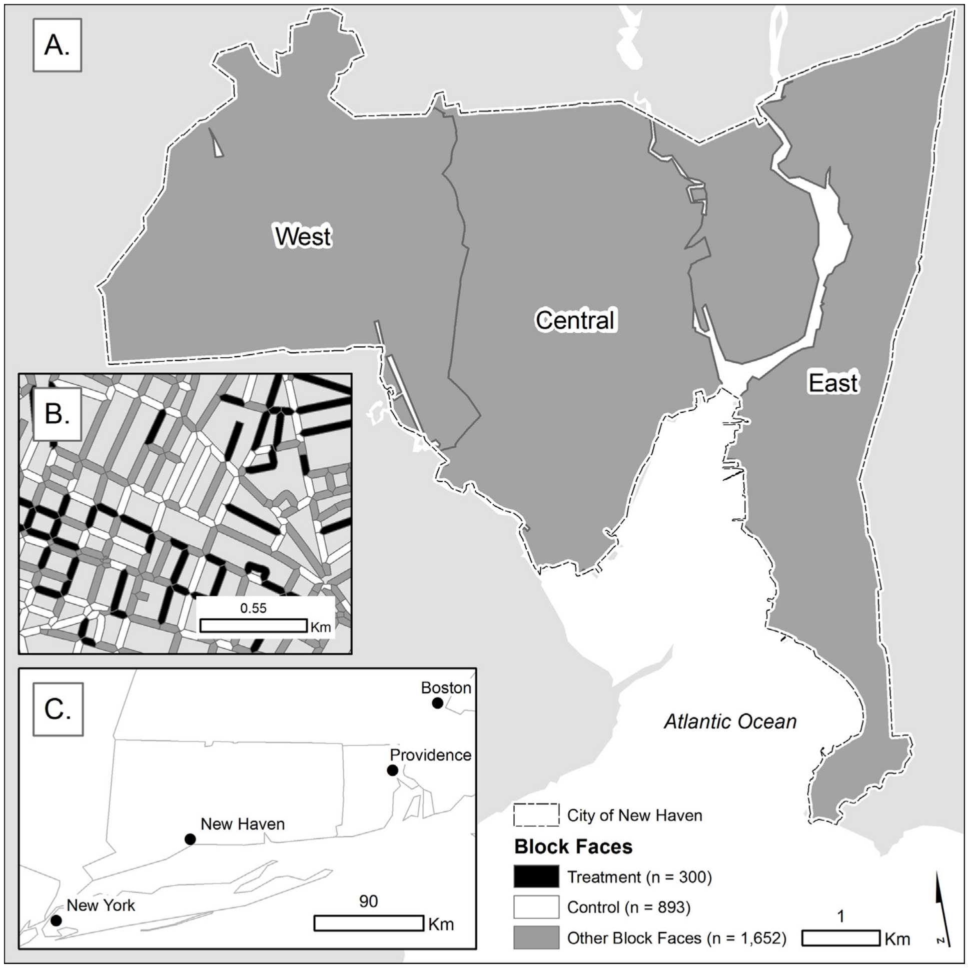

Fig. 1. Map of New Haven. The city was divided into three sections (West, Central and East) to help facilitate the case-control matching process. To ensure similarity, candidate controls had to be within the same section of the city (A), controls had to be greater than ¼ mile away from their corresponding treatment block face, but could be within that distance of another due to practical limitations (B). New Haven's location within southern New England (C).

$$V(Y_{it}|P_{it}, R_{it}, X_{it}) = E(Y_{it}|P_{it}, R_{it}, X_{it}) + E(Y_{it}|P_{it}, R_{it}, X_{it})^2 * \alpha$$

where Y_{it} is crime on block face i at time t. P_{it} is the pre-treatment (0)/post-treatment (1) term, and R_{it} indicates control (0)/treatment (1) status. Therefore β_3 is the DID coefficient for the interaction between pre-post and treatment-control ($P_{it} \times R_{it}$) and of principal interest to the research question. The analyses in Table 1 and the regression models were fit using Stata 14 (StataCorp LP, College Station, TX). Fig. 2 was created with R version 3.2.2 (2015-08-14) – "Fire Safety".

The first, base model did not include demographic covariates and therefore represents the unadjusted difference in differences estimates per crime type. In the second model, we added terms X_{it} to represent a series of independent sociodemographic control covariates: percent owner-occupied housing, median household income, education, and employment. In a third model, we added ξ_i, a block face-unit fixed effect, and δ_t, a time fixed effect, to control for unobserved unit characteristics and secular trends that might affect crime outcomes in each block face at given times. α represents the variance of the gamma-distributed random intercept. We report incidence rate ratios (IRR) instead of regression coefficients, to represent relative difference and to make interpretations easy.

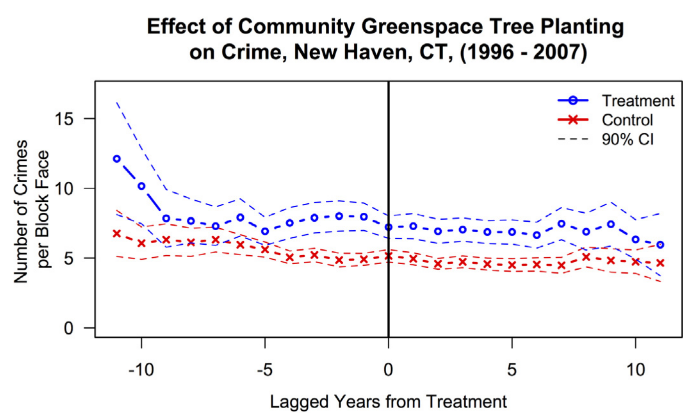

Fig. 2. Pre- and Post-treatment averages of all crimes for treatment and control groups.

2.3. Robustness checks

We ran two models as robustness checks to the three main negative binomial models. First, we added a term M_i to represent a pre-period mean outcome value to adjust for regression to the mean. In this model, we also adjusted sociodemographic covariates for regression to the mean. For a second robustness check, we estimated a Poisson model with Huber/White/Sandwich (also

Table 1
Crime and sociodemographic measures for treatment and control block faces.

Variable	Control Sites N = 893 Mean[a] (sd)	Treatment Sites N = 300 Mean[a] (sd)	Wilcoxon RankSum p-value
Crime Type			
AllCrime[b]	5.04 (7.49)	7.38 (8.73)	0.000***
Pre-period	5.41 (8.00)	7.83 (9.57)	
Post-period	4.76 (7.07)	7.02 (8.01)	
Violent	0.75 (1.51)	1.17 (1.89)	0.000***
Pre-period	0.78 (1.59)	1.17 (1.98)	
Post-period	0.72 (1.44)	1.16 (1.82)	
Property	2.86 (4.80)	3.89 (4.43)	0.000***
Pre-period	3.14 (5.30)	4.21 (4.93)	
Post-period	2.65 (4.36)	3.64 (3.99)	
Misdemeanor[c]	1.43 (2.71)	2.32 (3.92)	0.000***
Pre-period	1.49 (2.75)	2.45 (4.25)	
Post-period	1.39 (2.69)	2.22 (3.64)	
Demographic Variables			
Year 1990			
Percent Owner Occupied, %	32.83 (17.14)	31.32 (13.58)	0.568
Median Household Income, $	26,607 (8,891)	25,742 (7,916)	0.262
Percent w/ HS diploma, %	39.47 (19.49)	39.40 (17.02)	0.419
Percent Employed, %	67.08 (10.79)	67.08 (9.83)	0.579
Year 2000			
Percent Owner Occupied, %	28.79 (15.91)	29.00 (13.74)	0.850
Median Household Income, $	29,766 (10,090)	30,123 (10,287)	0.570
Percent w/ HS diploma, %	69.90 (13.04)	69.86 (12.55)	0.757
Percent Employed, %	85.39 (10.45)	85.20 (8.93)	0.197
Year 2006/2011			
Percent Owner Occupied, %	30.84 (17.26)	30.41 (13.45)	0.874
Median Household Income, $	40,146 (15,668)	37,674 (13,055)	0.016**
Percent w/ HS diploma, %	90.72 (9.93)	89.50 (9.77)	0.032**
Percent Employed, %	97.14 (3.14)	96.75 (3.71)	0.266

Crimes Sample sizes: pre-period (treatment: 1,569/ control: 4,645); post-period (treatment: 2,031/ control: 6,083).
[a] average crime incidents per block face.
[b] category includes violent, property, and misdemeanor crimes.
[c] category includes vandalism, prostitution, and narcotics crimes.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

called robust) standard errors instead to see whether the gamma-distribution-assumed random intercepts in the negative binomial models drove our reported results (Berk & MacDonald, 2008; Gould, 2011; Rabe-Hesketh & Skrondal, 2012). This alternative model also included sociodemographic covariates and fixed effects for block face-unit and time for comparability.

3. Results

3.1. Descriptive statistics after matching

Treatment and control block faces were not different at the $p < 0.01$ level in terms of sociodemographic indicators, except for median household income and percent of the population with a high school diploma which were higher among control block faces in 2006–2011 ACS data. The sociodemographic variables were also used as controls in the regression models. Block faces greened by Greenspace-affiliated community groups, however, had statistically significantly more crimes at the $p < 0.001$ level than their matched control sites for all crime types (Table 1).

Because the treated sites had more crime, before we conducted the main analyses we examined crime trends among treatment and control block faces over time. Fig. 2 shows the pre- and post-treatment trends of all crime averages for both treatment and control groups. We centered the treatment years of each block face at zero so that the negative values (−11 to −1) to the left represent pre-treatment years and the positive numbers (1 to 11) represent post-treatment years. Fig. 2 also shows that the parallel assumption of the DID design is roughly met; pre-period trends were largely similar among treatment and control groups. If pre-period trends were not similar, or "parallel", among treatment and control groups, post-period difference in trends would not be attributed to the treatment. However, mean values for all crime types were consistently and significantly higher at treatment compared to at control block faces at the $p < 0.001$ level (Table 1, Fig. 2).

3.2. Model outputs and robustness checks

DID estimates are shown in Table 2 as IRRs of crime counts. Model 1 shows the unadjusted DID estimates, and the other models show adjusted estimates. In general, whether positive or negative, the DID coefficients were small and not significant irrespective of the specification over the models. However, the DID estimates for All Crime suggested a minor decline post-treatment for Model 3 (p-value = 0.078) and Model 4 (p-value = 0.076), respectively. For the other crime types examined, all models showed no significant reduction in crime associated with community-planted street trees at the $p < 0.1$ level.

4. Discussion

A unique contribution of this study is to take advantage of quasi-experimental conditions to examine the potential effects of community-based street tree plantings on crime. Previous observational research in New Haven found a negative relationship between tree canopy and crime (Gilstad-Hayden et al., 2015), which corroborates findings from similar studies elsewhere (e.g. Deng, 2015; Donovan & Prestemon, 2012; Troy et al., 2012; Troy et al.,

Table 2
Adjusted-difference-in-differences effects of the impact of Community Greenspace planted trees on crime per block face, per year, in New Haven, CT, 1996–2007.

	Main Regression Models						Robustness-Check Regression Models			
	Model 1		Model 2A		Model 3		Model 2B		Model 4	
Crime Type	IRR (95% CI)	p-value	IRR (95% CI)	p-value	IRR (95% CI)	p-value	IRR (95% CI)	p-value	IRR (95% CI)	p-value
All Crime	1.019 (0.925, 1.123)	0.704	0.980 (0.893, 1.075)	0.668	0.951 (0.899, 1.006)	0.078*	1.020 (0.930, 1.119)	0.675	0.949 (0.896, 1.006)	0.076*
Violent Crime	1.063 (0.928, 1.219)	0.379	1.016 (0.891, 1.159)	0.807	0.96 (0.866, 1.059)	0.400	0.992 (0.870, 1.132)	0.908	0.948 (0.862, 1.042)	0.270
Property Crime	1.025 (0.928, 1.132)	0.626	0.991 (0.900, 1.090)	0.850	0.950 (0.892, 1.012)	0.114	1.042 (0.946, 1.148)	0.407	0.962 (0.902, 1.027)	0.245
Misdemeanor Crime	0.975 (0.866, 1.098)	0.676	0.951 (0.848, 1.065)	0.382	0.932 (0.850, 1.023)	0.139	1.002 (0.911, 1.103)	0.963	0.916 (0.822, 1.022)	0.118
Demographic Covariate?	No		Yes		Yes		Yes		Yes	
Fixed Effects Covariates?	No		No		Yes		No		Yes	
Regression to Mean Covariates?	No		No		No		Yes		No	
Model	Negative Binomial		Negative Binomial		Negative Binomial		Negative Binomial		Poisson with Robust SE	

Notes: 1. Negative Binomial models were specified with standard SE's. 2. Poisson models were specified with robust SE's. 3. IRR = Incident Rate Ratio. 4. CI = Confidence Interval (Lower, Upper).
* $p < 0.1$.

2016; Wolfe & Mennis, 2012). However, our quasi-experimental approach did not complement those findings, nor the findings from quasi-experimental research of greening interventions led by municipalities, non-profit groups or their contractors, in other places (e.g. Branas et al., 2011; Kondo et al., 2015a,b). In general, we found a null relationship between trees planted and crime on block faces per year at the $p < 0.05$ level. Increases in crime were not observed on treatment sites. There are several reasons that may explain these findings.

First of all contamination between the treatment and control block faces may have played a role. If there was a reduction in crime from the community-based tree plantings, it is possible that those effects could have spilled over to other nearby untreated sites. Although control block faces could not be within a ¼ mile of a particular treatment block face, it could have been within a ¼ mile of another treated block face (Fig. 1b). Imposing a constraint to make none of the control sites within a ¼ mile of a treatment block face would eliminate nearly all candidate block faces before considering the additional matching criteria. Our attempt to maintain comparability with similar DID research in Philadelphia, PA (Branas et al., 2011; Kondo et al., 2015b) and Youngstown, OH (Kondo et al., 2015a) was not possible in New Haven, CT. The Community Greenspace groups' efforts are too many, too diffuse, and New Haven is too geographically small; these groups have planted all over the city over the 12-year study period. There are also additional community greening activities in New Haven not captured in URI's database including notable gardening efforts from New Haven Land Trust. The Parks department also planted street trees during the study period, but the major *community-driven* plantings were from URI-affiliated community green space groups, which is the focus of this paper. Together–the possible spillover effects and other greening efforts–means the treatment and control groups are more similar to each other than is desirable with respect to the treatment, and would bias all results (positive or negative) toward the null if present (Aschengrau & Seage, 2008; Humphreys, Panter, Sahlqvist, Goodman, & Ogilvie, 2016).

A second possible reason for the null findings relates to selection bias among treatment sites. The decision of when and where to plant street trees was not within our control, and was not randomized. Instead the community groups designed and implemented the plantings based on their own goals and capacity. The selected locations had statistically significantly higher crime at the time of planting compared to their matched control sites (Table 1, Fig. 2). This violates the assumptions of DID analyses, but was unavoidable as well.

A third possible reason for the null findings concerns the operationalization of the tree planting as an intervention in the built environment. While quasi-experiments take advantage of events plausibly causally related to outcomes of interest, distinguishing between 'exposed' and 'unexposed' populations or geographic areas can be complex. Imprecise measurement of treatment, and of exposure to it, may have limited this study (Humphreys et al., 2016). Future research may better capture the nature of changes in the built environment as an intervention. For example, instead of two categories (treatment and control) ordinal or even continuous measures could be used to understand the gradation of exposure. Some groups plant just one street tree, and others plant entire blocks. For example, our analyses did not control for the number of street trees planted by a community group, just whether or not trees were planted. The abundance of street trees per block face was not examined either, because the needed data are not available. Moreover, not all of the trees survived throughout the study period (Jack-Scott et al., 2013; Troxel et al., 2013). Thus this study could not capture a possible dose-response effect on crime associated with street tree plantings. Measures that reflect that variation should be used in the future. A distance decay from intervention sites (spatially and temporally), or other more sophisticated weighting schemes for exposure to the intervention might be needed for understanding crime-urban greening relationships. Some types of quasi-experiments may need to treat exposure as a gradient from highly influential to only weakly associated. Existing GIS methods are sophisticated enough to generate more nuanced measures of exposure (Humphreys et al., 2016), provided that the requisite data on the many types of greening data are collected and made available. See, for example, the stewardship mapping and assessment project or "STEW-MAP" (Svendsen et al., 2016).

5. Conclusion

In this study we examined the possible effect of community-planted street trees on crime in New Haven, CT, a mid-sized city with a relatively high crime rate. These analyses were motivated, in part, by a gap in the existing literature with respect to bottom-up urban greening and crime relationships, despite the growing literature on top-down greening initiatives and crime. A DID analysis of 12 years of incident-level crime data, summarized to block faces per year, provided a null finding. No statistically significant before-after, treatment-control results were found for a range of crime types, using a variety of statistical modeling techniques. The reductions in crime shown in the All Crime Models 3 and 4 at the $p < 0.1$ level could have arisen from multiple comparisons; we found a null relationship between trees planted and crime on block faces per year at the $p < 0.05$ level. Contamination of control sites, selection bias of the treatment sites, and/or the imprecise operationalization of what constitutes a treatment may explain our findings. Use of either quasi-experimental or experimental techniques to study the impact of trees on crime and violence or health outcomes require highly detailed record-keeping and monitoring of tree-plantings and tree inventories across government agencies, community groups, non-profits and other stakeholder groups. To assess the impact of tree-plantings on surrounding communities, study design and analysis methods that can address the high level of spatial and temporal variation of tree-plantings will be necessary. Future research should consider more carefully quasi-experiential conditions to better leverage events that are plausibly related to phenomena of societal interest such as crime, health and safety (Humphreys et al., 2016). It is important to note that while we did not find the hypothesized outcome, the process of tree planting and the resulting street trees provide many other social and environmental benefits.

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